

# Informing parametric risk control policies for operational uncertainties of offshore wind energy assets

Anastasia Ioannou<sup>a,\*</sup>, Andrew Angus<sup>b</sup>, Feargal Brennan<sup>c</sup>

<sup>a</sup> Cranfield University, School of Water, Energy and the Environment, Renewable Energy Marine Structures - Centre for Doctoral Training (REMS-CDT), Cranfield, Bedfordshire, MK43 0AL, United Kingdom

<sup>b</sup> Cranfield University, School of Management, Cranfield, Bedfordshire, MK43 0AL, United Kingdom

<sup>c</sup> University of Strathclyde, Department of Naval Architecture, Ocean & Marine Engineering, Glasgow, G4 0LZ, United Kingdom

## ARTICLE INFO

### Keywords:

Offshore wind energy  
O&M cost modelling  
Loss of revenue  
Weather-related risks  
Risk control

## ABSTRACT

The aim of this paper is to investigate uncertainties present during operation of offshore wind (OW) energy assets with a view to inform risk control policies for hedging of the incurring losses. The parametric framework developed is subsequently applied across a number of different locations in the South East Coast of the UK, so as to demonstrate the effect of weather conditions and resulting downtime on a number of operational Key Performance Indicators (KPIs), such as downtime due to planned and unplanned interventions, wind farm availability, Operation and Maintenance (O&M) costs and power production losses. Higher availability levels were observed in areas closer to shore of the specified region, while the distribution of O&M cost per MWh generated demonstrated a general trade-off of higher power generation in locations farther from shore due to better wind speed profiles and higher O&M costs, as a result of the decreasing vessels accessibility. The proposed methodology aspires to contribute to the development of better-informed risk control policies, through parametrically estimating the probability of exceedance curve of the production losses of an OW farm and indicating appropriate thresholds to be considered, so as not to exceed a maximum level of risk.

## 1. Introduction

Most relevant decisions throughout planning, construction and operation of Offshore Wind (OW) energy assets made by market agents involve a significant level of risk due to technical conditions and project externalities (Ioannou et al., 2017a,b). Mathematically, risk can be expressed as the product of the probability of occurrence of an event and the consequences associated with its outcome: Risk = Probability-Consequence, while according to (ISO, 2009) risk is defined as the effect of uncertainty on a project's objectives. Generally, loss of revenue risk (as a result of project delays, turbine components damage/losses during transport, construction and operation) can substantially affect the value of the asset. During the construction phase, unfavourable weather can result in delay of the commissioning date due to lack of accessibility of installation vessels (which bear specific working limits for various marine operations). During the operation phase, in the occurrence of a failure, weather-related risks can increase the total downtime of the wind farm by impeding the access of the support vessels dispatched to perform maintenance activities, leading to revenue losses. Both cases can lead to significant impact in cash flows and

the project's ability to meet debt service requirements. Within the context of this study, weather-related risks refer to the effect (i.e. potential energy production losses) of the random nature of key sea state variables, namely the wave height and wind speed, whose exceedance beyond a threshold can influence the operability of the asset (i.e. due to limited accessibility for maintenance).

In order to estimate the loss of revenue risk, the downtime of the asset needs to be estimated as accurately as possible through modelling the planned and unplanned maintenance activities during the O&M phase of the asset. The development of high fidelity models would assist in the calculation of the total availability, power production losses and O&M costs throughout the service life of the asset, which typically account for approximately 30% of the Levelised Cost Of Electricity (LCOE) in OW energy (Carroll et al., 2016a; Ioannou et al., 2018).

Most OW O&M models currently available are used to inform project developers/owners on the expected costs and performance of their assets. They typically use turbine and Balance of Plant (BOP) reliability data coupled with meteorological prediction models in order to predict the operational state of the wind farm throughout its service life and the maintenance activities required. In general, existing models and tools

\* Corresponding author.

E-mail address: [a.ioannou@cranfield.ac.uk](mailto:a.ioannou@cranfield.ac.uk) (A. Ioannou).

<https://doi.org/10.1016/j.oceaneng.2019.02.058>

Received 28 August 2018; Received in revised form 7 January 2019; Accepted 17 February 2019

Available online 01 March 2019

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allow the modelling and simulation at a wind farm level, considering various failure types for each wind turbine. Each failure type belongs to a certain maintenance category, which determines the weather limitations and vessel, crew, and time needed for the repair. The repair is performed when the simulated weather conditions allow for it so that the faulty turbines do not produce power until the repair is finished. The models also keep track of availability of vessels, crews, and spare parts, such that the influence of the availability vessels and crews on the availability and maintenance costs of the overall plant can be assessed. Common outputs of such models comprise the downtimes per sub-system/failure type and per maintenance stage, the wind farm/turbine availability, the total number of failures occurred, the number of spare parts and the revenue losses, among others.

Commonly available O&M models include the ECN O&M tool (Rademakers et al., 2009) and the NOWICob tool (Hofmann and Sperstad, 2013; Welte et al., 2017), among others (Asgarpour, M.V.d.P., 2014; Dinwoodie et al., 2013; Feuchtwang and Infield, 2013; Rangel-Ramirez and J.D.S., 2008; Scheu et al., 2012). A comprehensive review of OW O&M models is provided in (Hofmann, 2011; Martin et al., 2016), while a benchmarking study comparing/verifying four O&M simulation models (namely the Strathclyde CDT, NOWICob, Uis Sim Model and ECUME) by means of a reference wind farm is presented in (Dinwoodie et al., 2015).

The present paper aims to inform risk control policies addressing weather-related uncertainties during the operational phase of OW energy investments for hedging of the incurring losses. The novelty of the present work lies on: 1) the visualisation through scatter plots of O&M-relevant KPIs of OW energy projects installed in a region of interest through the application of an in-house parametric O&M model, and 2) the estimation of the probability of exceedance of a certain production loss threshold due to weather-related uncertainties, allowing insurers to quantify the entailed risk.

The proposed framework is parametrically applied in a reference region, so as to demonstrate the effect of weather conditions and resulting downtime on a number of operational Key Performance Indicators (KPIs), such as wind farm availability, O&M costs per produced MWh and power production losses. The proposed framework for calculating O&M KPIs incorporates latest databases of failure rates and cost components throughout the O&M phase of the wind farm, while it also allows rapid simulations for a number of locations within a region allowing development and visualisation of parametric expressions. Above analysis aspires to contribute to the development of better-informed revenue loss risk control policies, through parametrically estimating the probability of exceedance of a specified revenue loss threshold.

The rest of the paper is set out as follows: Section 2 presents an overview of risk control options available for renewable energy assets, along with an introduction to key reliability concepts widely used in the O&M cost analysis of OW turbines. Section 3 presents the framework developed for the calculation of operational KPIs. Subsequently, results from the application of the framework to a baseline wind farm installed at a specific location are presented in section 4, followed by the parametric estimation and illustration of O&M related KPIs across a number of locations in the South East Coast of the UK. Furthermore, this section expands the applicability of the proposed method to estimate the expected production losses due to the downtime of the wind farm and estimate the probability of exceedance of a pre-determined threshold, which would activate a potential risk control policy. Finally, section 5 summarises the findings of this work.

## 2. Power production uncertainties and risk control options

### 2.1. Risk control options for renewable energy assets

Investing in renewable energy assets, e.g. an Offshore Wind Farm (OWF), is typically subjected to downside risks, which is the

combination of the probability of occurrence of a negative event and its associated financial effect (International Standardisation Organisation, 2009). The likelihood and impact of negative events are reflected in the financing costs (quantified by the Weighted Average Cost of Capital (WACC)) of the technology; higher investment risk tends to increase both the bank's interest rates and the equity owners' return expectations. Furthermore, considering the fact that renewable energy technologies are typically capital-intensive investments, their lifecycle costs are very sensitive to an increase in financing expenditures (Schmidt, 2014). It can, therefore, be concluded that financial risk mitigation can play an important role in reducing the LCOE of the technology.

General risk control options include: i) risk retention, ii) risk avoidance, iii) risk mitigation and iv) risk transfer. Companies retain a risk, when they have determined that transferring the risk is costlier than covering all or part of the losses out of their reserve budget (also called self-insurance) or when they decide to consciously take a risk to potentially achieve a higher gain. Avoiding the risk implies deciding not to get involved in a high-risk investment or operating within a (geographic or operational) region where the underlying hazard is not present. Mitigating the risk involves limiting the impact of a risk by taking appropriate measures. Finally, risk transfer involves the contractual shifting of a risk from one party to another, usually from the project owner to one or more insurance providers.

As far as the risk insurance market of OW energy is concerned, there is currently a number of commercial risk control products that are expanding as the technology becomes more established (UNEP, 2004). Construction is a phase of the lifecycle of an OW asset, which involves considerable risks, mainly due to the likely occurrence of incidents during the transportation and/or installation of wind turbines and BOP components. Such risks can be mitigated through effective project management and contracting; however, project owners tend to seek to extend their risk coverage to protect their investment against Delay in Start-Up (DSU), or the Advanced Loss of Profit (ALOP) incurred through the inability of the construction contractor to commission the project on time. Developers can claim back lost revenues resulting from delays in construction (Swiss Re & Bloomberg New Energy Finance, 2013). Another common risk transfer product available is the Construction All Risks (CAR), covering physical loss and damage during the construction phase of a project (UNEP, 2004).

Following the construction of the wind farm, project owners often rely on manufacturer yield/availability warranties by signing an O&M contract that guarantees a certain uptime or availability level; if the minimum yield levels are not met, the O&M contractor will be liable for availability Liquidated Damages (LDs) (Clifford Chance, 2017). The O&M contract comprises the most common risk control method ensuring the provision of spare parts and maintenance labour. The loss of revenue due to component failure or natural catastrophe is critical for OW owners (U.S. Department of Energy, 2013). In example, faults in the transformer of the offshore substation, which from a reliability perspective is the 'weak link' of the wind farm, may result in the shut down of the whole wind farm inducing large financial losses. It is, therefore common apart from the manufacturer's warranties (which usually last for 5 years, after which the contract can either be renewed or the owner proceeds with alternative O&M risk coverage ways) to undertake Business Interruption (BI) coverage to insure against losses that are not already covered by O&M contracts.

Loss of revenue can also be induced by severe weather, preventing vessels to access OW turbines to perform scheduled or unscheduled maintenance. In such cases, the owner of the asset can purchase an insurance product to hedge the financial impact of adverse weather on the project. These risk control products dealing with the inability of the Operations and Maintenance Contractor to gain access to the OWF Facility through short or sustained periods of unusually high waves can be financially mitigated through the use of parametric (finite risk) products. These products are called parametric because they are triggered by a weather-related parameter such as the significant wave

height or the wind speed (Swiss Re & Bloomberg New Energy Finance, 2013). Such products are gaining popularity as investors become more risk averse.

## 2.2. The concept of availability

The service life of the wind farm asset typically consists of uptime and downtime periods, with uptime representing the intervals during which the turbine is able to produce energy and downtime the time that the turbine stops working, as a result of a subsystem failure until the turbine is restored. Time-based availability,  $A_{time}$  (Eq. (1)) can be defined as the ratio of the total uptime of the wind farm to the total time in consideration (sum of uptime and downtime), while production-based availability,  $A_{production}$  (Eq. (2)) is estimated as the ratio of the energy actually produced to the amount of energy that would ideally be produced based on actual wind speeds and site conditions (DNV GL, 2017; Scheu et al., 2017).

$$A_{time} = \frac{Uptime}{Uptime + Downtime} \quad (1)$$

$$A_{production} = \frac{Actual\ energy\ produced}{Energy\ production\ potential} \quad (2)$$

Fig. 1 demonstrates the Mean Time to Failure (MTTF), which equals the uptime period when the turbine is able to produce power and the Mean Time to Repair (MTTR), which reflects the total downtime of the wind farm and includes a number of activities related to planned and unplanned maintenance. Activities listed during the downtime can be divided into passive and active downtime. Passive downtime is related to the activities required until the execution of the actual maintenance activity (active downtime). Improving availability can be achieved through decreasing passive downtime through better planning.

## 3. Development of an efficient model for calculating operational KPIs

### 3.1. Overview of the model

The proposed model structure was determined following a state-of-the-art literature review of existing O&M models which allowed for the comprehensive modelling of the decisions made during the O&M phase of the asset.

The main modules of the integrated O&M analysis framework are: (1) the failure modelling module, (2) the weather modelling module, and (3) the cost modelling module.

The failure modelling module is further divided into the MTTF estimation (namely the uptime of the asset) and the MTTR estimation throughout the planned and unplanned maintenance operations (namely the downtime of the asset). The mean time to failure calculation is based on the annual failure rates, while the planned and

unplanned maintenance operations require data related to the resources required for the repairs. Resulting downtime depends on the availability of the required vessels, technicians, weather window, spare parts, mission organisation time, duration of navigation and repair, as well as the required number of technicians' shifts.

The weather modelling module enables the prediction of the future sea states, namely future significant wave heights and wind speeds. This module can, therefore, determine the expected power generation when the wind turbine is in operation through the turbine's power curve and the predicted wind speeds. The expected power generation, in turn, is introduced into the O&M cost module to estimate the actual loss of revenue taking into account both the downtime and the expected wind speeds. Weather conditions play an important role in the total downtime of the wind farm, as when the related parameters surpass the set wave height and wind speed limits of the vessels, travelling to wind turbines and accessing them becomes impossible. Therefore, unfavourable weather conditions will delay repairs and, thus, will increase downtime and decrease the wind farm's availability.

The cost modelling module takes into account the actual duration of all stages required to perform the repair and maintenance operations and uses vessel and crew day-rates, along with material costs to predict the total O&M cost. Other outputs of the model are the time-based and production-based availability, and the power production losses.

It should be noted that the development of decisions for the different steps of the model have taken into consideration not only the accuracy of the calculation but also the computational efficiency required so as to allow a serial execution of simulations which is relevant to the comparative analysis which is the aim of this study. A high level verification based on the results of published cases has been performed, while further calibration of the model for more accurate results can take place through a specific case study.

### 3.2. Failure modelling module

#### 3.2.1. Estimation of mean time to repair (MTTR)

The MTTF is equivalent to the uptime of the turbine and it can be calculated through the failure rates of the subsystems, as illustrated in Fig. 2 with the orange coloured boxes (U2–U8). All symbols are summarised in the Appendix. In this study, the repair categorisation of Reliawind project (Garrad Hassan, 2007) was adopted which classifies repair classes of subsystems into minor repairs, major repairs and major replacements.

A total of 19 subsystems of the wind turbine were considered, while data used for the application of the model on failure rates, average repair times, average material costs and number of required personnel were retrieved from (Carroll et al., 2016b). As shown in Fig. 2, the MTTF of each turbine ( $t_r$ ) is initially calculated based on the failure rates of their subsystems ( $s$ ) (U2–U5). Assuming that the reliability of the turbine follows an exponential distribution, the Probability of Failure (PoF) can be expressed as:

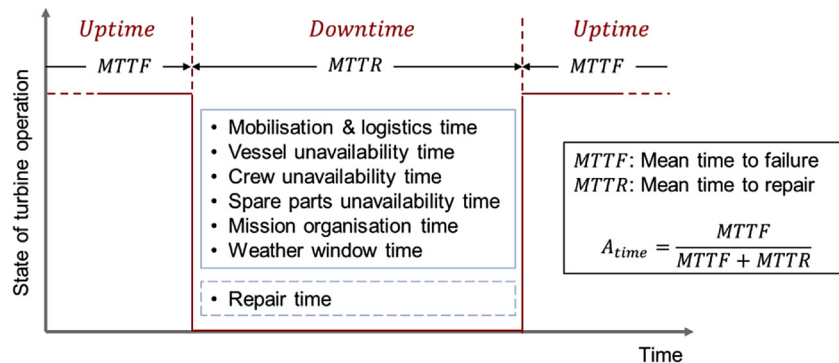


Fig. 1. Operational states of the turbine.

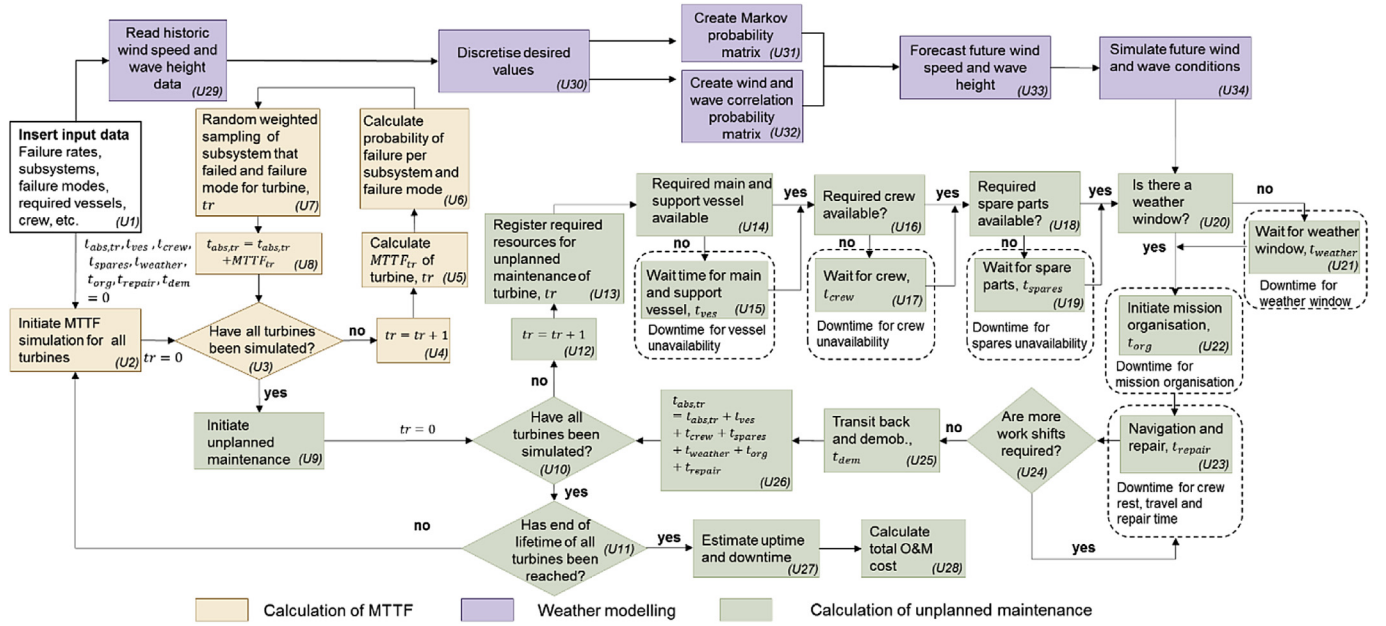


Fig. 2. Unplanned maintenance flowchart.

$$PoF_{tr} = 1 - \text{Reliability} = 1 - e^{-\lambda_{tr} \cdot t} \quad (3)$$

$$t = MTTF_{tr} = -\frac{1}{\lambda_{tr}} \ln(1 - PoF_{tr}) \quad (4)$$

where,  $\lambda_{tr} = \sum_{s=1}^{Subsyst} \lambda_s$  is the sum of the failure rates of each turbine's subsystems in series. Monte Carlo simulation is, then, performed to generate numerous random PoF and subsequently returns an average  $MTTF_{tr}$  value for each wind turbine. Once the MTTFs are calculated, Equation (5) can be used to estimate the probability of occurrence of each subsystem's failure (U6), as:

$$PoF_s = 1 - e^{-\lambda_s \cdot MTTF_s} \quad (5)$$

where,  $\lambda_s = \sum_{k=1}^{Repair\ class} \lambda_k$  is the sum of the failure rates of the different repair classes ( $k$ ) of the subsystems (namely, the minor repairs, major repairs and major replacements) and  $MTTF_s$  is the MTTF of each subsystem. Once the probabilities of each subsystem's failure are known, the model performs random weighted sampling (U7) to determine which subsystem will fail once the MTTF has elapsed along with the repair class, which is also randomly selected following the same logical process. Apart from the MTTF calculation, the model calculates the absolute time set of the simulation ( $t_{abs, tr}$ ), which is interpreted as the actual time from the beginning to the end of life of the wind farm and is composed by the MTTF and the calculated downtimes (U8). The duration of the individual activities during planned and unplanned maintenance are added to the absolute time set, enabling the calculation of the uptime and downtime of the turbine and registering the time when a certain failure happens.

### 3.3.2. Planned and unplanned maintenance

Unplanned (corrective) maintenance is carried out following the occurrence of a failure on the turbine or the BOP, which may affect several turbines. The procedure after the occurrence of a new failure is illustrated in Fig. 2 with the green coloured boxes (U9–U28). Once a failure has occurred on the first turbine (i.e. when the MTTF elapses), the unplanned maintenance is initiated (U9) and the turbine instantaneously shuts down. The required resources - namely, the number and type of main and special vessels, number of crew and materials, depending on the subsystem and the repair class - are, then, registered for the specific turbine (U13). The maintenance process begins with the availability check of the required main and support vessels (U14–U15),

followed by the check of the required number of crew (U16–U17) and subsequently, the spare parts (U18–U19). It is assumed that a predetermined number of vessels can operate in the wind farm, which will be available to access the wind turbine that failed if the weather conditions allow so and the same applies for the predetermined number of personnel and spare parts needed for the repair. If, however, all predetermined available vessels/crew/spare parts are occupied, the failure remains unresolved and the check is repeated once the required number of vessels/crew/spare parts are released from the previous mission. All required resources can also be inserted by the user as per each subsystem and repair class. Once the required vessels, crew and spare parts are available, the weather conditions are checked (U20–U21). The weather window is sufficient as long as the significant wave height and the wind speed conditions at the wind farm site (which are forecasted with a 3-h time step) are below the operational threshold limits of the vessels commissioned throughout the whole intended time offshore. Although this assumption may be a little conservative, consideration of higher resolution sea state forecasts that would enable shorter term forecasting would significantly increase the complexity and computational effort of the model; nevertheless, the parametric analysis featured in this work requires multiple simulations to be realised, hence increasing the computational effort would render the model non fit for purpose. Subsequently, the organisation of the mission (U23), including the mobilisation of the vessel(s) (if required), take place. Once the crew accesses the subsystem that failed, the repair is carried out (U24); it is assumed that one work shift lasts for up to 12 h, which includes the total repair time, transitioning from harbour to the site and vice versa, as well as a mid-shift break. In case that more than one shifts are required, the crew returns to harbour and the mission restarts 12 h later (U25). When the damage is restored, the wind turbine starts producing power again, and the MTTF of the subsystem is reset to its original value. Finally, the transit back to the harbour and the demobilisation time need to be accounted to estimate the end of the mission (when the vessel and crew becomes available for the next mission), which will affect activities described in U14–U17. At that point, the absolute time of each wind turbine is revised by adding the durations of all previous unplanned maintenance activities, namely: the waiting time for vessel/crew/spares availability, the lack of weather window, the organisation time of the mission, and the crew rest, navigation and repair activities, as shown in Fig. 2 (U26). Above process is repeated for all wind



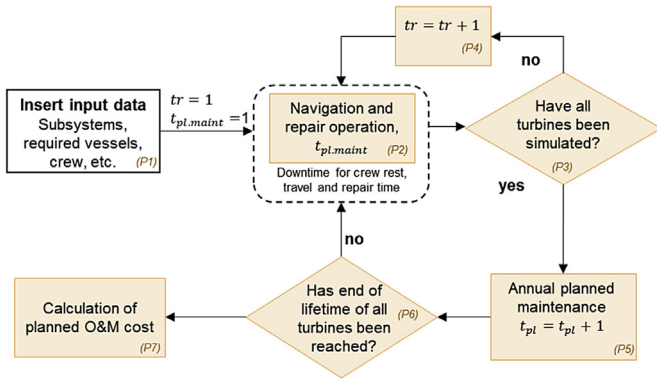


Fig. 3. Planned maintenance flowchart.

turbines (U10). Once the absolute total time set of each turbine equals the predetermined service life of the wind farm (U11), the simulation stops and O&M-related key performance indicators, such as total uptime, downtime, availability and O&M cost per MWh generated, can be derived (U27–28).

Planned maintenance (else calendar-based maintenance) operations are carried out periodically and deal not only with one subsystem of the wind turbine, but with groups of (or all) subsystems of each wind turbine during each charter. Planned maintenance can be scheduled ahead of time, during periods of favourable weather conditions when delays to missions due to exceedance of vessels' safety limits (weather window downtime) are not likely to occur, so that the availability of the wind turbine and amount of generated electricity is affected the least possible. The same applies for vessels, crew and spare parts unavailability downtimes. In this analysis, calendar based maintenance is assumed to take place every one year ( $t_{pl.maint}$ ) with a deviation of  $\pm 1$  month, to simulate the real life operations. Downtime due to planned maintenance is assumed to originate exclusively from the navigation and repair time together with the potential downtime due to crew rest, as shown in Fig. 3. An iteration process takes place until all wind turbines ( $tr$ ) have been maintained (P5) and reached the end of their service life by monitoring the absolute time set of each turbine which considers the MTTF and the downtime due to planned and unplanned maintenance. In this analysis, it is assumed that planned maintenance can only restore minor repairs, i.e. once each mission terminates the mean time to failure of minor repairs is reset. It is expected that unplanned maintenance will incur higher downtimes in relation to planned maintenance considering the longer expected downtimes and types of maintenance activities.

### 3.3. Weather modelling

As described in the previous sections, predicting weather conditions for the operational lifetime of an OWF is crucial to predict its availability. If wave height and wind speed conditions exceed vessels' safety thresholds, transit from harbour to the wind farm is not possible leading to delays in performing repairs, thus increasing downtime and decreasing the wind farm's availability (Scheu et al., 2018).

Commonly used methods for generating sea state time series comprise Gaussian and Langanian approaches for short term wave modelling, Autoregressive Moving Average (ARMA) methods and Markov-based models. In this study, the Markov chain process was chosen due to the fact that it works well for long term forecasting and can capture persistence of sea state parameters. Additionally, it is a method widely applied in literature (Anastasiou and Tsekos, 1996; Hofmann and Sperstad, 2013; Scheu et al., 2012) and can handle conditional probability distributions.

Overall steps of the discrete time Markov chain process used for the weather forecasting method are illustrated in Fig. 2 with the purple

coloured boxes (U29–34). To this end, historic weather datasets from 1992 to 2017 with a 3-h time step were retrieved from BTM ARGOS database (BTM ARGOS, 2017). Discrete time Markov chains method is based on having a finite number of states in a system and estimating the probability,  $p_{ij}$  of state  $i$  to evolve into state  $j$ . Markov probability matrices are generated for each month, to account for seasonality, as shown below:

$$P(\text{sea state parameter})_{\text{month}} = \begin{pmatrix} p_{11} & p_{12} & \dots & p_{1n} \\ p_{21} & p_{22} & \dots & p_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ p_{n1} & p_{n2} & \dots & p_{nn} \end{pmatrix}_{\text{month}} \quad (6)$$

where,  $p_{ij}$  equals the number of transitions of sea state parameter  $i$  to  $j$ , divided by the total number of times, state  $i$  appears. As such, initially, the weather data is discretised with a specified resolution (Fig. 2, U30). A time step of 3 h is considered for the forecast, during which wind speed and wave height are assumed to remain constant. Based on the probabilities of each transition matrix, the wave height for the starting month is randomly selected and, successively, all sea state conditions are predicted as a function of the previous state and the transition probability.

### 3.4. Cost modelling

The cost modelling module gathers the data recorded during each iteration, which are required to estimate the O&M cost. For unplanned maintenance of wind turbines, the time that a failure occurs is registered with reference starting point the beginning of operation of the wind farm. Further, the subsystem that failed and the type of failure will define the required main and support vessels (to match the correct day rates) and the number of crew members required for the repair. Downtimes of crew unavailability, spare parts unavailability, weather window, navigation time and demobilisation time are taken into account and assigned to the respective day rates of vessels, crew, cost of materials, mobilisation and demobilisation costs, to estimate the total O&M cost.

## 4. Results and discussion

### 4.1. Baseline wind farm

#### 4.1.1. Characteristics of wind farm

The baseline case is a representative wind farm located in European waters and its characteristics are summarised in Table 1. The integrated O&M cost estimation framework was applied to the baseline wind farm and across a number of different locations in a region by the South East Coast of the UK.

Weather data were obtained from the BTM ARGOS database for a set of 204 different locations with latitude and longitude coordinates ranging between  $[0.000^\circ, 2.667^\circ]$  and  $[50.000^\circ, 53.667^\circ]$ , respectively, covering the South East Coast of the UK as illustrated in Fig. 4. This region was selected due to its high concentration of currently operating and under construction Round 1, 2 and 3 wind farms (The Crown Estate, 2017).

Existing ports near the afore-mentioned set of 204 different locations of the focus region were identified from 4C offshore (4C Offshore,

**Table 1**  
Baseline wind farm characteristics.

Parameter	Value
Number of turbines	140
Turbine rated power	3.6 MW
Service life	25 years
Cut in speed	4 m/s
Cut out speed	25 m/s

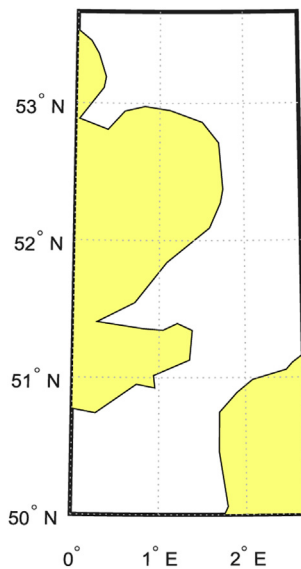


Fig. 4. Focus region located in the South East Coast of the UK.

Table 2

Coordinates of nearby ports (in decimal degrees).

Port	Longitude	Latitude
Wells	52.954	0.853
Great Yarmouth	52.583	1.735
Lowestoft	52.473	1.755
Harwich Navyard	51.948	1.288
Sheerness	51.443	0.748
Ramsgate	51.327	1.412
Newhaven	50.790	0.055
Shoreham	50.831	0.238

2018) and their coordinates are summarised in Table 2. It was assumed that these ports provide their adjacent wind farms with maintenance support services. To this end, the distances of all ports from all potential OWF locations were calculated and the port having the shortest distance from a particular OWF location was assumed to be the base port of this location, serving its maintenance operations.

#### 4.1.2. Assumptions on the operating cost components

Cost components taken into consideration in the present study comprise the cost of main and support vessels, crew and materials. Herein, material is anything that is used or replaced in the turbine; from consumable materials to whole replacement parts such as full generators. The required cost parameters of the maintenance vessels are summarised in Table 3. The material costs are adopted from Carroll et al.'s publication (Carroll et al., 2016b) while the vessel and crew day rates as well as the cost of materials used in the present study were adopted from a recent publication of the authors (Ioannou et al., 2018). All costs were assumed to be fixed throughout the 25 service life of the

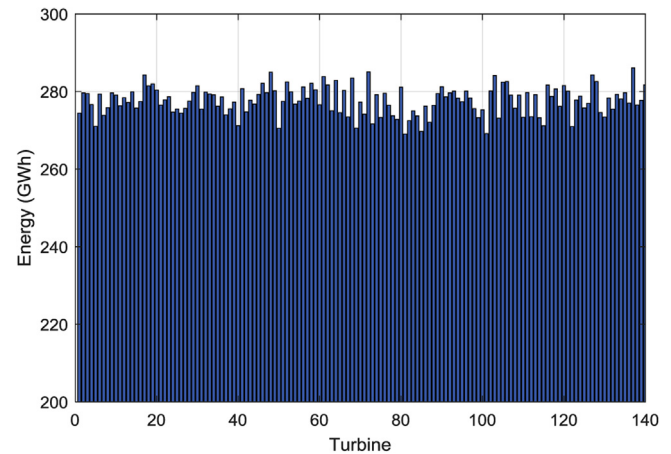


Fig. 5. Power output per each turbine.

asset, so as to reduce the complexity of the model. To estimate the revenue loss due to the downtime of the wind farm, a fixed price of 100 £/MWh was assumed throughout the 25 year service life of the wind farm asset.

#### 4.2. Risk-based revenue loss modelling

##### 4.2.1. Operation and Maintenance results for a specific location

The model was initially applied for the prediction of the operational KPIs of the baseline wind farm installed in a single location with co-ordinates [0.000°, 50.334°]. For the modelling of the future weather conditions on location [0.000°, 50.334°], weather data obtained from BTM ARGOS were discretised with a resolution of 0.2 m for wave height and 1 m/s for wind speed data, resulting in a finite number of possible values, namely 33 (ranging from 0 to 6.4 m) and 25 values (ranging from 0 to 24 m/s), respectively. The mean wave height of the dataset was calculated 1.08 m and mean wind speed 10 m above sea level 6.83 m/s.

The power output (for the 25 years of operation) of each of the 140 turbines as well as the breakdown of downtimes are illustrated in Fig. 5 and Fig. 6, respectively.

Total power produced was calculated 38872 GWh and the total downtime  $2.7887 \cdot 10^6$  h with a power-based availability of 90.1% and a time-based availability of 88.9%. The downtime due to weather unsuitability had the highest share of the total downtime (25.1%) followed by the repair time (22.2%) and the spare availability downtime (16.8%).

The temporal O&M costs throughout the service life of the wind farm are shown in Fig. 7 for unplanned maintenance of both wind turbines and the BOP, as well as for planned maintenance. Total wind farm O&M cost during the entire service life was estimated at £686.5 million.

Due to the difficulty in obtaining long term data from operational wind farms (as a result of the newly developed industry and the

Table 3

Characteristic values of vessels used during the O&M phase of the wind farm (Source: (Ioannou et al., 2018)).

Vessel type	Technician space (#)	Vessel speed (knots)	Weather limits		Mob./Demob. Cost (k£)	Mob./Demob. Time (h)	Day rate (k £/day)
			Sign. wave height (m)	Wind speed (m/s)			
Crew transfer vessel	12	26	1.8	16	–	–	3.25
Jack-up vessel	–	10	2	10	405	720/48	112.6
Helicopter	6	130	99	20	4.7	8/4	4.7
Diving support vessel (DSV)	–	16	2	25	185	360	60
Cable laying vessel	–	14	1	10	44	720	90

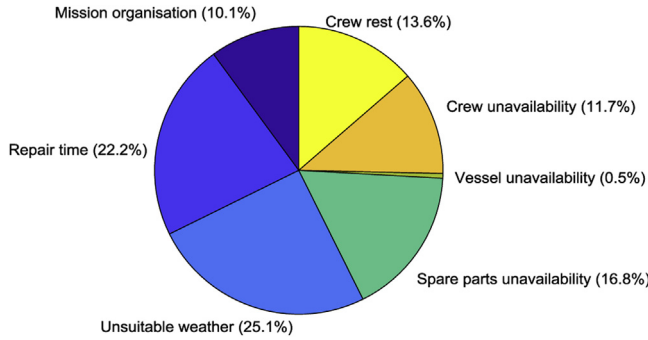


Fig. 6. Breakdown of downtimes.

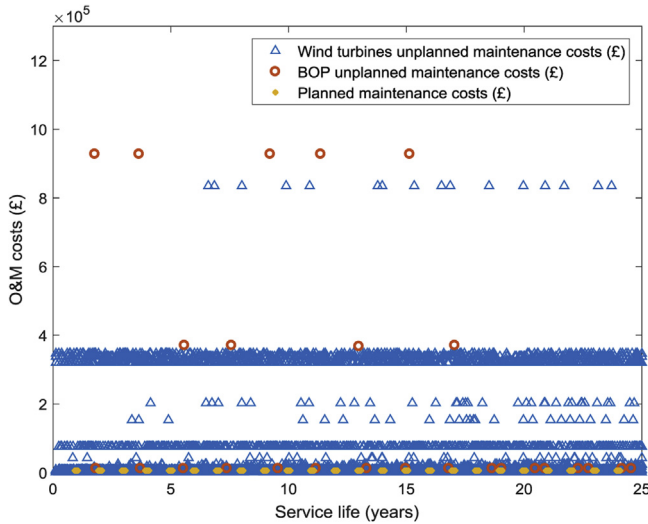
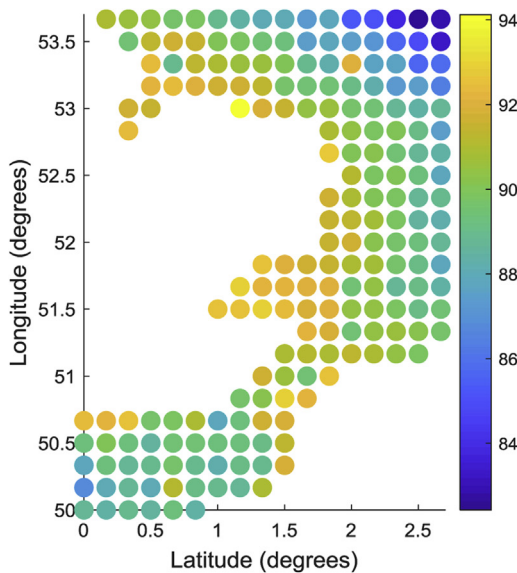
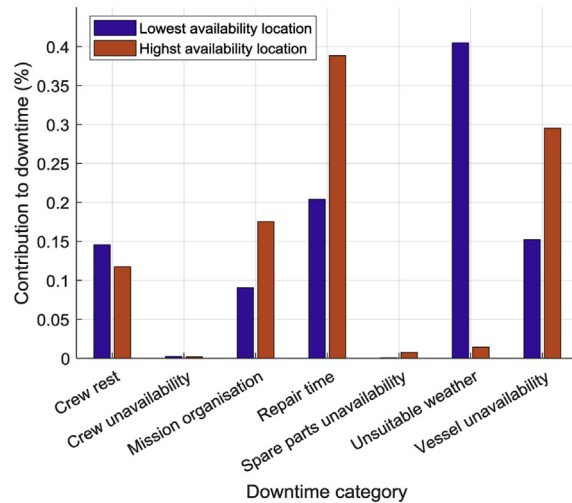


Fig. 7. O&amp;M costs throughout the service life of the wind farm.

motivation of turbine manufacturers and operators to keep their competitive advantage by not distributing information related to reliability and cost), validation of O&M models is a difficult task. Furthermore,



(a)



(b)

Fig. 8. Production-based availability (%) around the focus area of the study and (b) contribution of downtime categories to the highest and lowest availability locations.

available benchmarking studies such as the one made in (Dinwoodie et al., 2015) highlight significant differences in the calculated O&M KPIs across four O&M tools compared in their study. However, an attempt was made by the authors to compare results of the developed model with results derived as part of the recent work of Martin et al.'s (Martin et al., 2016), which also studied the operational availability of wind farms located in the south east coast of the UK and performed simulations for three OWF case studies. Mean annual wave height (1.02 m) and wind speed 10 m above sea level (7.15 m/s) were also relatively close to the reference case study of the present work. The range of availability was estimated between 84% and 92%, with an average of 89%. Results have shown acceptable agreement as both studies have shown relatively lower values of availability compared to generic values reported in literature, which is due to the overall weather potential of the region. It also has to be noted that deviations between the two models can be justified due to the more up to date failure rate databases used in the present study.

#### 4.2.2. Parametric estimation of operational KPIs

Subsequently, the model was applied for 204 locations in the South East Coast of the UK (illustrated in Fig. 4), using the respective historic weather data for each set of coordinates retrieved from the BTM AR-GOSS database. A convergence study was conducted to determine the size of the Monte Carlo sample for the calculation of MTTF of each turbine and the model iterations to ensure the robustness and efficiency of the model. The averaging of the outputs derived from 1000 Monte Carlo simulations and 5 iterations of the code were determined to allow for the generation of robust results. Accordingly, a number of location-specific colour-coded plots, illustrating resulting operational KPIs across the whole region, were generated.

The production-based wind farm availability results are plotted in Fig. 8(a) for each of the 204 sets of coordinates under investigation. Higher availability levels can be observed in areas closer to the coast of the specified region (noting that half a degree is equivalent to a distance of approximately 56 km). This can be attributed to the smaller distances between the port and the wind farm site, as well as the lower magnitudes of significant wave height and wind speed limits, improving the accessibility of the maintenance vessels for the performance of unplanned maintenance, hence reducing the total downtime of the asset.

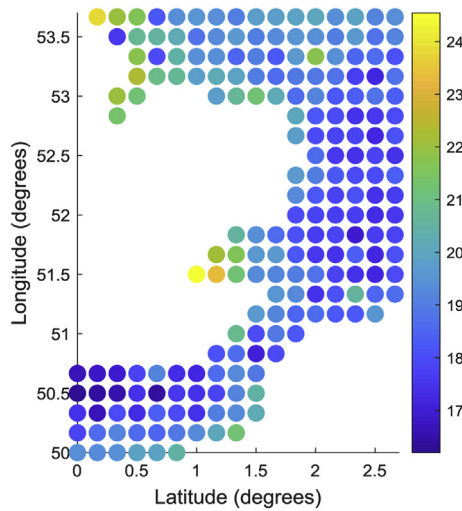


Fig. 9. Undiscounted O&M cost per MWh around the focus area of the study.

Results demonstrate a smooth transition from high availability values in locations closer to the coast to gradually decreasing farther from shore. Nevertheless, a number of outliers can be observed, for example in the location point  $[2.000^\circ, 53.334^\circ]$ , where an availability peak is noted; this can be explained as the result of measurement uncertainty of the historic met ocean data. Fig. 8 (b) illustrates the breakdown of downtimes for the location with the lowest and highest availability. Weather downtime appears to have the greatest contribution to the total downtime for the lowest availability location, while repair time is the main contributor for the highest availability location.

Fig. 9 illustrates the total (undiscounted) O&M cost per produced MWh, revealing a more uniform distribution of unit cost in relation to the availability values across the different locations. This is due to a trade-off of higher power generation due to better wind speed profiles and higher O&M costs due to decreasing accessibility of vessels for maintenance operations. For example, a hypothetical wind farm installed at point  $[1.000^\circ, 51.500^\circ]$  appears to reach an availability level of 92.6% (Fig. 8(a)) in return of high unit costs amounting to 24.5 £/MWh (Fig. 9) as a result of the poor wind speed profile resulting in low power production. Nevertheless, exceptions of this observation can be found, for example, in the areas positioned in the southern part of the specified region, where high availability together with relatively low unit costs can be observed. This observation can potentially lead to the conclusion that these regions can offer a good balance of availability versus costs. However, it has to be noted that other factors such as geotechnical conditions, environmental impact assessment studies and other parameters need to be taken into account before determining the suitability of a location for the installation of a wind farm (Mytilinou et al., 2018; Mytilinou and Kolios, 2019).

Finally, the expected total power production loss due to the wind farm downtime is plotted in Fig. 9. Production loss reflects the total revenue loss due to downtime, as it is calculated by subtracting the power produced during uptime from the potential power produced both during uptime and downtime (wind speed profile of the location is also taken into consideration); it is therefore a parameter with a great impact on the financial performance of the investment. The revenue loss plot was found to follow a similar to the availability plot pattern, with locations closer to shore indicating lower revenue potential losses due to the reduced downtime of the wind farm.

#### 4.2.3. Weather-related risk control policy options

Traditional insurance products available for renewable energy projects typically protect against natural disasters, such as storms, earthquakes and hurricanes (Grossi et al., 2005), as well as physical losses and damages to the plant/asset during the construction and

operating phases (UNEP, 2004). Furthermore, academic literature on the effects of weather-related risks on OW energy projects also focuses on analysing the effect of extreme weather events (Barabadi et al., 2016; Becerra et al., 2018; Lamraoui et al., 2014). However, risk management against the effect of seasonal fluctuations in climatic conditions, such as variation in wind speeds, temperature and wave height is becoming more relevant as investors are inclined to reduce their risk exposure. Weather-related risk hedging products are usually financial contracts which can be executed in the form of insurance or weather derivatives structured as swaps, futures and options that are based on a weather related index (Li, 2018); in the case of OW, significant wave height and wind speed could be relevant weather related indices. The seller of the weather derivative bears the risk of potential financial losses as a result of the weather conditions in exchange of an upfront premium. If the pre-determined limit of the index is surpassed, over a specified period, the project owner is compensated the downtime financial losses.

The index based policy structure has the advantage of simplicity, although there may exist some ambiguity in terms of the actual financial impact caused by the exceedance of the specified threshold. In the case of OW, for example, exceedance of the threshold of the significant wave height limit over a specified period of time may not necessarily lead to financial losses. On the contrary, power production loss due to downtime could be a risk index easier-to-translate into resulting revenue losses over a period of time, while relevant data can be retrieved by the Supervisory Control and Data Acquisition (SCADA) systems installed in the wind farm.

Fig. 11 illustrates the cumulative power production losses summed on a monthly period over the service life of the baseline wind farm installed in the location  $[0.000^\circ, 50.334^\circ]$ . A threshold of 45000 MWh power production loss over the period of a month was assumed, above which the buyer of the risk transfer product is compensated for the revenue loss corresponding to this threshold. The estimation of the premium should be based on the probability of exceedance of the specific limit. With a 5.6% monthly probability of exceedance, the risk of the investor is estimated (in terms of production losses)  $45000 \times 5.6\% = 2520$  MWh. Assuming a fixed price of 100 £/MWh, the maximum premium that the buyer would be willing to pay is therefore £ 252000 per month.

The Exceedance Probability (EP) curve is used by insurers to estimate the Probable Maximum Loss (PML) for a portfolio of investments in a given period of time. The PML is a bespoke risk metric, and is

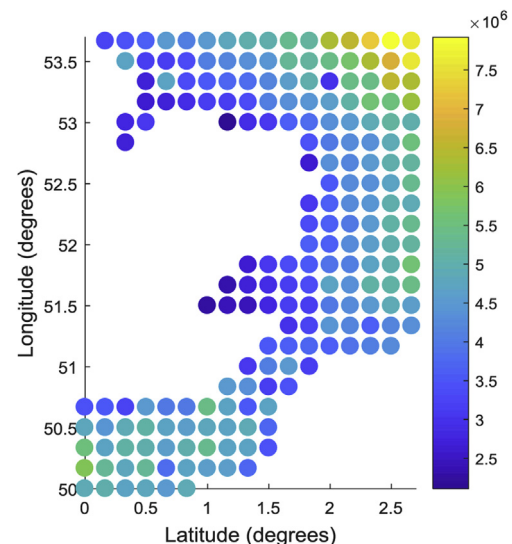


Fig. 10. Production loss (in MWh) scatter plot of wind farm around the focus area of the study.



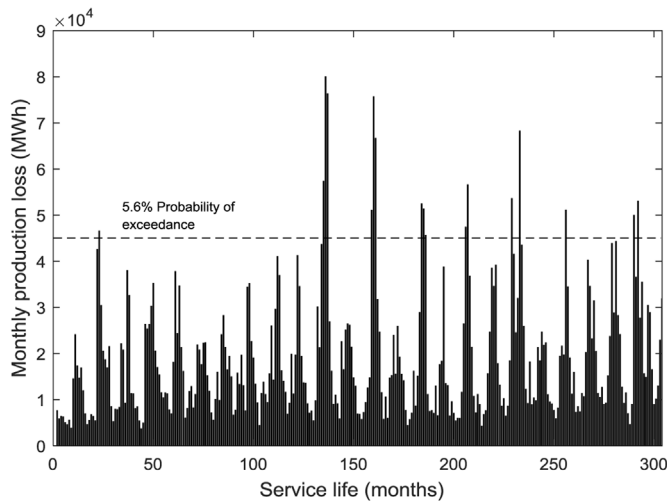


Fig. 11. Monthly power production losses as a function of time for the location with coordinates  $[0.000^\circ, 50.334^\circ]$ .

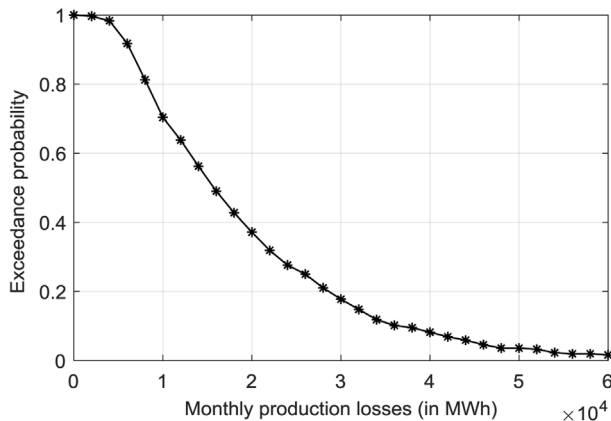


Fig. 12. Exceedance probability curve.

associated with a probability of exceedance reflecting the insurer's acceptable level of risk. As such, the insurer can use the EP curve to determine the magnitude of loss at the desired probability of exceedance level. In Fig. 12, the monthly EP curve of the reference wind farm is demonstrated. The EP curve can also assist the distribution of losses between stakeholders. As such, the project owner would retain the first part of the loss (i.e. the deductibles), for example losses up to 45000 MWh, while the insurer covers monthly production losses occurring in excess of this amount.

Setting the above threshold of monthly power production losses (i.e. 45000 MWh) across all sets of coordinates of the designated region, the distribution of the exceedance probabilities is illustrated in Fig. 13. For areas closer to the coast, the probability of exceedance does not surpass the level of 6%, while in areas farther from shore probability reaches 18%. Comparing the scatter plot of probability of the production loss exceedance threshold with the production losses one (in Fig. 10), it becomes evident that the amount of power production losses throughout the service life of the asset is not necessarily proportional to the entailed risk of surpassing a threshold set on a monthly or even annual basis. This map can provide a basis for screening which locations are likely to incur higher insurance premiums for weather related parametric risk control products.

Insurance policies are typically valid for a specified period of time defined in the insurance policy contract, varying from a few weeks to a number of years. It can, thus, be deduced that the magnitude of risk transferred to a third party greatly depends on the coverage period set

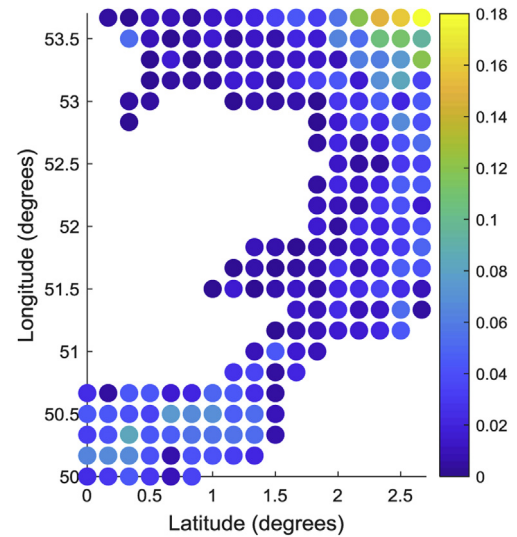


Fig. 13. Probability of exceedance of monthly power production loss threshold (45000 MWh/month).

by the contract. Specifically for OW energy assets, the persistence of the weather conditions can be detrimental on the resulting financial losses and by extension on the compensation required by the risk control policy.

Above application assumed that the risk control policy will be activated once the cumulative energy production losses within a reference period of one month surpass a specified threshold (45000 MWh). Through the EP curve, appropriate production loss thresholds can be identified by insurers, so as not to surpass a maximum risk level over the reference period of the risk control policy, adjusting their exposure to risk up to a desired level.

## 5. Conclusions

There is a number of industries whose operations can be impacted by the varying weather conditions and the OW industry is certainly one of them. Although the traditional weather related risk transfer products available are mainly employed to protect against catastrophic events, there is currently an increasing interest in hedging against seasonal weather fluctuation risks in order to minimise their impact on the financial performance of the investment. Protection against weather risk was originally included as a clause embedded in contracts for unforeseen weather conditions, but is now becoming a bespoke financial instrument to hedge the risk of the resulting financial losses, currently offered by insurance companies and brokers (Willis Towers Watson, 2018).

In this paper uncertainties present in the operational stage of OW investments are investigated systematically with a view to inform risk control policies for hedging of the incurring losses. For the estimation of operational KPIs, the latest databases of location-specific environmental conditions, failure rates and required repair resources are integrated together with discrete time Markov chains for forecasting future sea states. The model is firstly applied to a reference wind farm installed in a specific location to test the applicability of the model and verify its results. Then, the model is applied to a set of locations in the South East Coast of the UK to derive scatter plots of aforementioned KPIs, such as cost per MWh and power production losses, indicating the effect of weather and maintenance downtime throughout the O&M phase of the asset's lifecycle. Further to the calculation of power production losses, the probability of exceedance of a specified power production loss threshold was estimated across all locations of the South East Coast, deriving insights regarding the distribution of the risk level of financial losses due to weather and maintenance downtime across the designated

region.

It was observed that there is a trend for higher production-based availability levels in areas closer to the coast of the specified region. Furthermore, the scatter plot of O&M cost per MWh generated, demonstrated a more uniform pattern across the different locations indicating that there is a trade-off of higher power generation in locations farther from shore due to better wind speed profiles and higher O&M costs, as a result of the decreasing accessibility of vessels for performing maintenance operations. Production losses distribution was found to follow a pattern similar to the availability one, with locations closer to shore displaying lower potential production losses due to the reduced downtime of the wind farm. Production losses can reflect the total revenue loss due to downtime. To this end, it was chosen as the most relevant parameter to demonstrate the financial risk induced by weather and maintenance downtime. It was highlighted that the amount of power production losses throughout the service life of the asset is not necessarily proportional to the entailed risk of surpassing a set threshold.

In order for the developed model to be versatile, allowing for iterative simulations, a number of assumptions were considered which are acceptable for the comparative nature of the present study. These assumptions could be further considered in future studies which could focus on absolute calculation of KPIs. For example, the weather limits considered for each vessel can be modelled in greater detail distinguishing the limits for the vessel transit and the repair of the failure. Furthermore, from the repair identification until the asset becomes unfunctional (i.e. stops working) some residual capacity still exists; future work could focus on modelling this concept considering PF intervals.

Finally, the proposed methodology can be used by insurers and relevant stakeholders to produce the EP curve of the production losses of an OWF, indicating appropriate thresholds to be considered for a specific reference period (e.g. cumulative monthly, weekly or yearly production losses), so as not to exceed a maximum level of risk. In this way, risk control policies can be better informed, allowing the insurers to adjust their exposure to risk up to a desired level.

## Acknowledgment

This work was supported by grant EP/L016303/1 for Cranfield University, the University of Strathclyde and the University of Oxford, Centre for Doctoral Training in Renewable Energy Marine Structures (REMS) (<http://www.rems-cdt.ac.uk/>) from the UK Engineering and Physical Sciences Research Council (EPSRC). This work has also received funding from Supergen Wind Hub, grant number: EP/L014106/1.

## Appendix

### Nomenclature

#### Indices

$i, j$	Different sea states
$k$	Repair class (minor repairs, major repairs and major replacements)
$n$	Number of sea states considered
$s$	Subsystem of turbine
$tr$	Turbine

#### Variables

$A_{production}$	Time-based availability (%)
$A_{time}$	Production-based availability (%)
$MTTF_s$	MTTF of subsystem, $s$ (h)
$MTTF_{tr}$	MTTF of turbine, $tr$ (h)
$PoF_{tr}$	Probability of failure of turbine, $tr$

$p_{ij}$	Probability state $i$ evolves into state $j$
$t_{abs, tr}$	Absolute time set of the simulation (h)
$t_{crew}$	Downtime due to unavailability of crew (h)
$t_{dem}$	Demobilisation and transit back to the harbour time (h)
$t_{org}$	Downtime due to mission organisation (h)
$t_{repair}$	Downtime for crew rest, travel and repair time (h)
$t_{spares}$	Downtime due to unavailability of spares (h)
$t_{ves}$	Downtime due to unavailability of main and support vessel (h)
$t_{weather}$	Downtime due to unavailability of weather window (h)
$\lambda_k$	Failure rate of repair class, $k$ (failures/turbine/year)
$\lambda_s$	Failure rate of subsystem, $s$ (failures/turbine/year)
$\lambda_{tr}$	Failure rate of turbine, $tr$ (failures/turbine/year)

#### Abbreviations

ALOP	Advanced Loss of Profit
BI	Business Interruption
BOP	Balance of Plant
DSU	Delay in Start-Up
EP	Exceedance Probability
KPIs	Key Performance Indicators
LCOE	Levelised Cost of Electricity
LDs	Liquidated Damages
OWF	Offshore Wind Farm
PML	Probable Maximum Loss
WACC	Weighted Average Cost of Capital

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